MicroarrayTechnology

National Human Genome Research Institute

AFTER THE SEQUENCE:

WHOLE GENOME APPROACHES TO

BIOLOGICAL QUESTIONS

GENE EXPRESSION

GENE VARIATION

GENE FUNCTION

PUBMED literature on DNA microarrays

1050

3.5 X average increase per year

412

124

1   6   8   35

1995   2001

No. of publications per year

National
Human
Genome
Research
Institute

Development of Microarrays

| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |

Schena et al. Science 270:467

• Robotic high density printing of cDNAs

• Fluorescence detection

Development of Microarrays

1995	1996	1997	1998	1999	2000	2001	2002

DeRisi et al. Nat. Gen. 14:457

Schena et al. PNAS 14:1675

- Application to human cells

- Expression pattern related to tumorigenesis And T cell function

Lockhart et al. Nat. Biotech. 14:1675

- Oligonucleotides synthesized in situ

Cancer Genetics Branch

Development of Microarrays

1995	1996	1997	1998	1999	2000	2001	2002

Lakshari et al. PNAS 94:13057

Wodicka et al. Nat Biotech 13:1359

- Complete genome analysis: yeast

- Spotted DNA and oligos

Cancer Genetics Branch

Development of Microarrays for Cancer Research

1995	1996	1997	**1998**	1999	2000	2001	2002

Khan et al. Cancer Res 58:5009

• Cancers of the same type cluster.

Eisen et al. PNAS 95:14863

• Two dimensional clustering.

Kononen et al. Nat Med 4:844
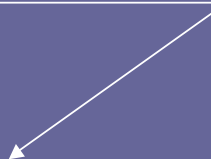
• Tissue microarrays.

Pinkel et al. Nat Gen 20:207

• CGH BAC arrays.

Development of Microarrays

1995	1996	1997	1998	**1999**	2000	2001	2002

Khan et al. PNAS 96:13464

• Expression program elicited by oncogene.

Golub et al. PNAS 286:531

• Formal diagnostic classifier.

Several sample clustering papers.

Development of Microarrays

| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |

Bittner et al. Nature 406:536
- Class discovery within a cancer type.

Cancer Genetics Branch

Development of Microarrays for Cancer Research

| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |

Bittner et al. Nature 406:536
- Class discovery within a cancer type.

Cancer Genetics Branch

Development of Microarrays

| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |

Bittner et al. Nature 406:536
- Class discovery within a cancer type.

Alizadeh et al. Nature 406:503
- Class discovery correlating with outcome.

Perou et al. Nature 406:747
- Class discovery in breast cancer.

Development of Microarrays

| 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 |

Numerous publications addressing

- Class discovery and classification.
- Diagnostic classifiers.
- Biological/genetic correlations.
- Outcome correlations.
- Mathematical tools.

MICROARRAY TERMINOLOG

- **Feature--an array element**

- **Probe--a feature corresponding to a defined sequence**

- **Target--a pool of nucleic acids of unknown sequence**

Kinds of array elements

- **Synthetic Oligonucleotides**

- **PCR products from**

  Cloned DNAs

  Genomic DNA

- **Cloned DNA**

Microarray Manufacture

• Printing

Prepare cDNA probes

"Normal"   Tumor

RT
Label with
Fluorescent Dyes

Combine
Equal
Amounts

Hybridize
probe to
microarray   SCAN

Prepare microarray

Microarray Manufacture

- **Printing**
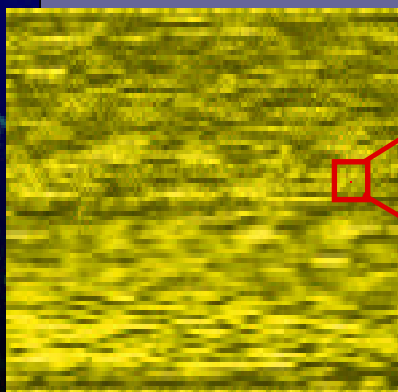
- **Synthesis *in situ***

MICROARRAY READOUT

Determine quantity of target bound to each probe in a complex hybridization

- **Must have high sensitivity, low background**

- **High spatial resolution essential**

- **Dual channel capability preferred**

DNA Microarray Applications

- **Resequencing**

  Mutations

  Polymorphisms

BRCA1 Coding Region Array

V1713A

T
G
C
A

5254 5255 5256 5257 5258 5259 5260

Oligonucleotide Array Design

Target

C

Surface Probes

Length

A

25

C

25

G

25

T

25

A
C
G
T

Perfect Match Probe

SINGLE NUCLEOTIDE POLYMORPHISM

AGGTTACCAGTA

AGGTTGCCAGTA

OCCUR ABOUT 1: 1250 BASES

SINGLE NUCLEOTIDE POLYMORPHISMS

- Polymorphic SNPs occur approximately every 1 kb in the human genome.

- Dense SNP maps provide a basis to design microarrays for genome scanning

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LABELLING SNPs

Genomic DNA
↓ multiplex PCR

Unlabeled amplicons
↓ primer extension

Labeled amplicons
↓ pool, denature, dilute into buffer

Hybridize to microarray

SNP CHIP*

*Wang et al.
Science 280:1077
1998

A/A homozygote   A/C heterozygote   C/C homozygote

Query Base

Cutler DJ et al. Genome Res. 2001 11:1913-25.

ACCURACY OF SNP CHIP

Table 3. ABACUS SNP Detection and Genotyping Accuracy

A. Accuracy of autosomal SNPs detection

	Verified	Total Possible
Singleton SNPs	17	17
Non-singleton SNPs	91	91
Total SNPs	108	108

B. Number of autosomal SNPs electronically verified

Number of SNPs electronically verified	371

C. Accuracy of autosomal genotype calls

Number of verified homozygous genotype calls	1515
Number of incorrect homozygous genotype calls	0
Percent correct homozygote calls	100.00%
Number of verified heterozygous genotype calls	423
Number of incorrect heterozygous genotype calls	3
Percent correct heterozygote calls	99.30%

D. Accuracy of haploid genotype calls

Number of bases sequenced (6X coverage)	17,423
Number of bases different from microarray chip calls	0
Percent of bases identical	100.00%

Cutler DJ et al. Genome Res. 2001 11:1913-25.

Cancer Genetics Branch

SNP CHIP FOR ALLELIC IMBALANCE

Primdahl H et al. J Natl Cancer Inst. 2002, 94:216-223

Cancer Genetics Branch

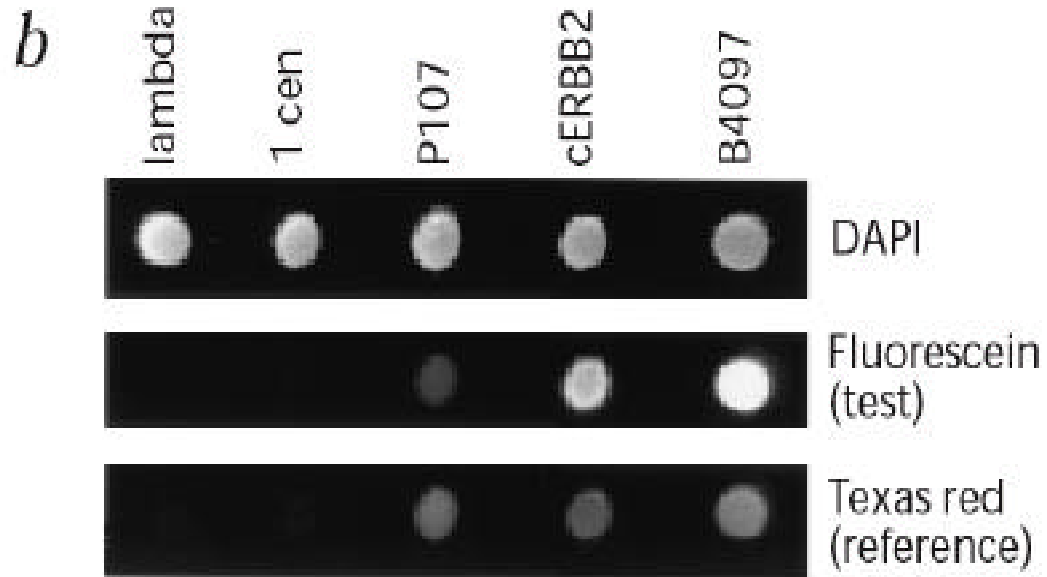# DNA Microarray Applications

- **Resequencing**

    Mutations
    Polymorphisms

- **Gene copy number**

Gene Copy Number

- **Array format CGH**

- **Large insert clones**
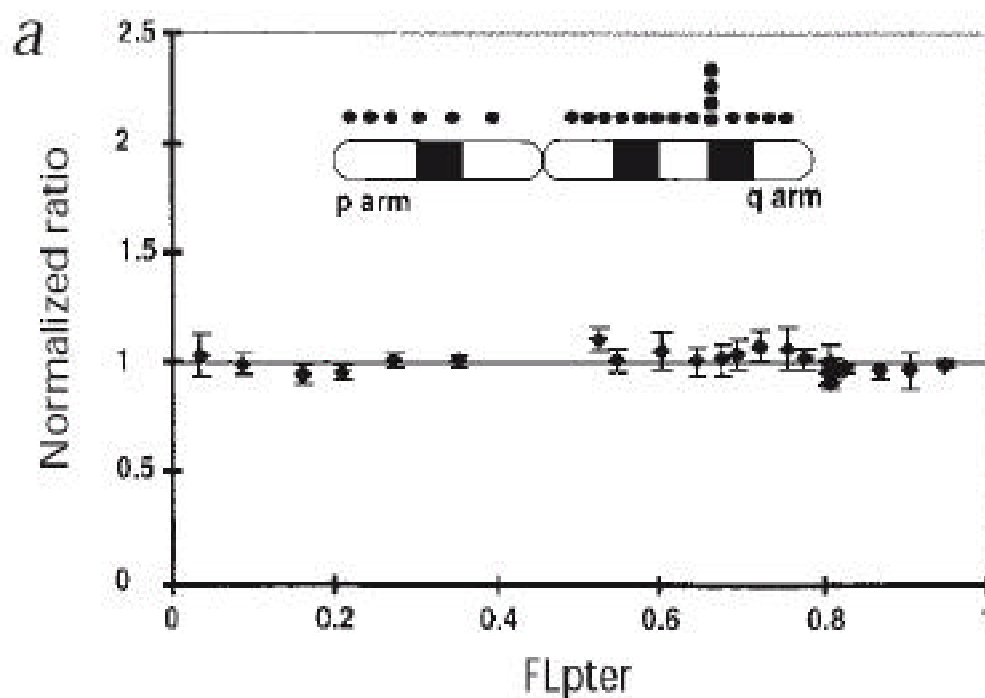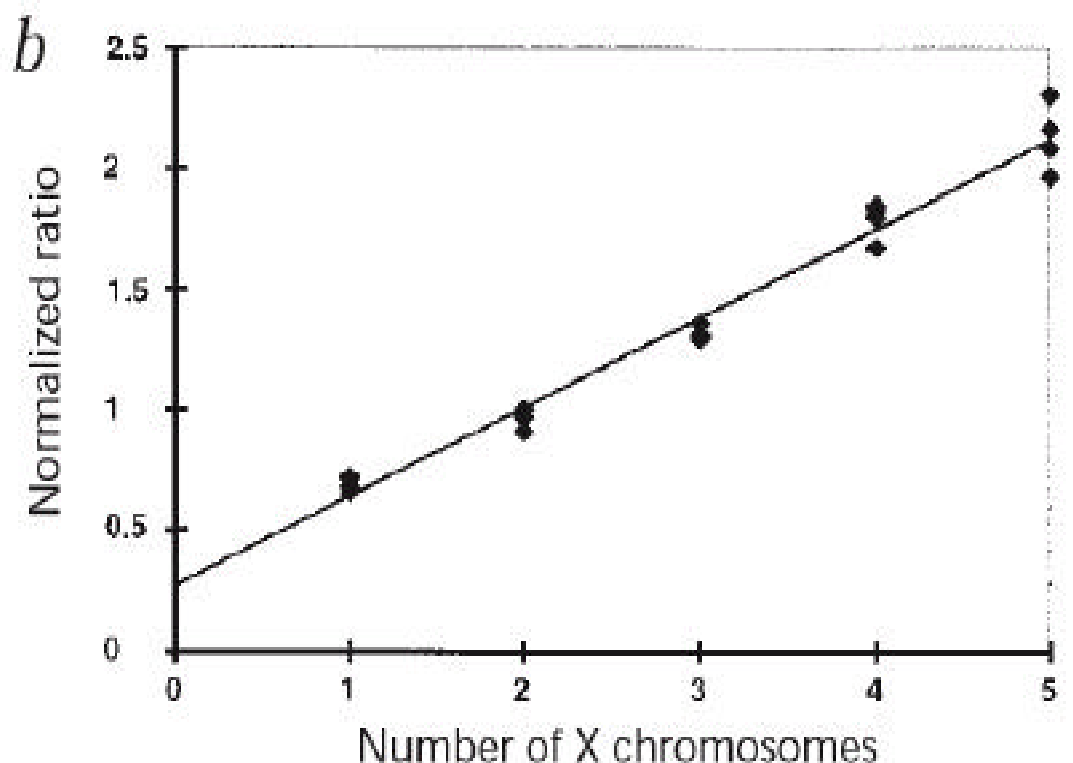
- **cDNA clones/exons**

CGH BAC ARRAYS

Pinkel D et al., Nature Genetics 20, 207 - 211 ,1998.

Cancer Genetics Branch

CGH BAC ARRAYS

Pinkel D et al., Nature Genetics 20, 207 - 211 ,1998.
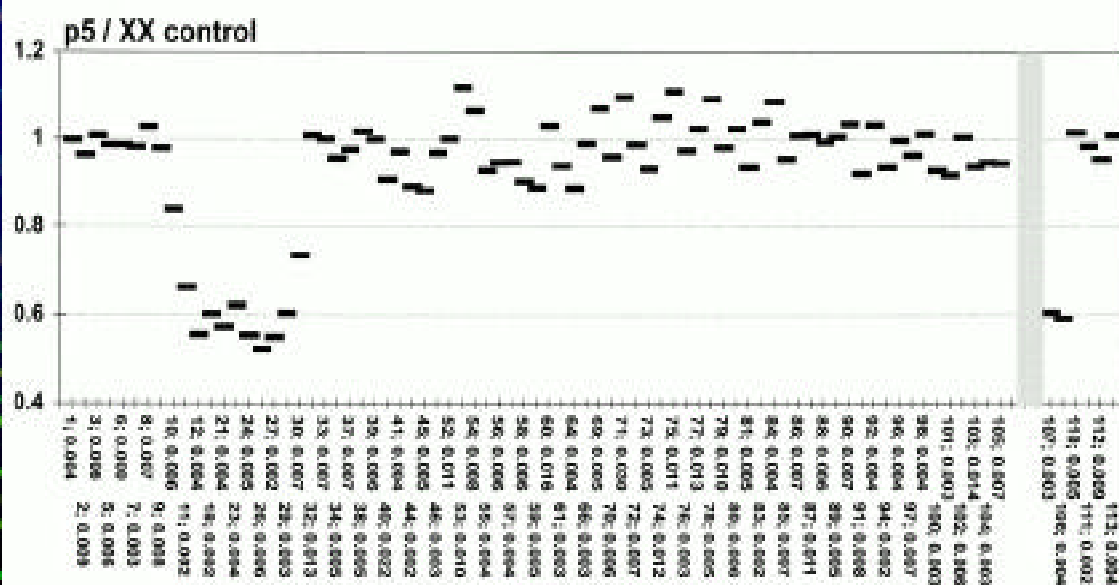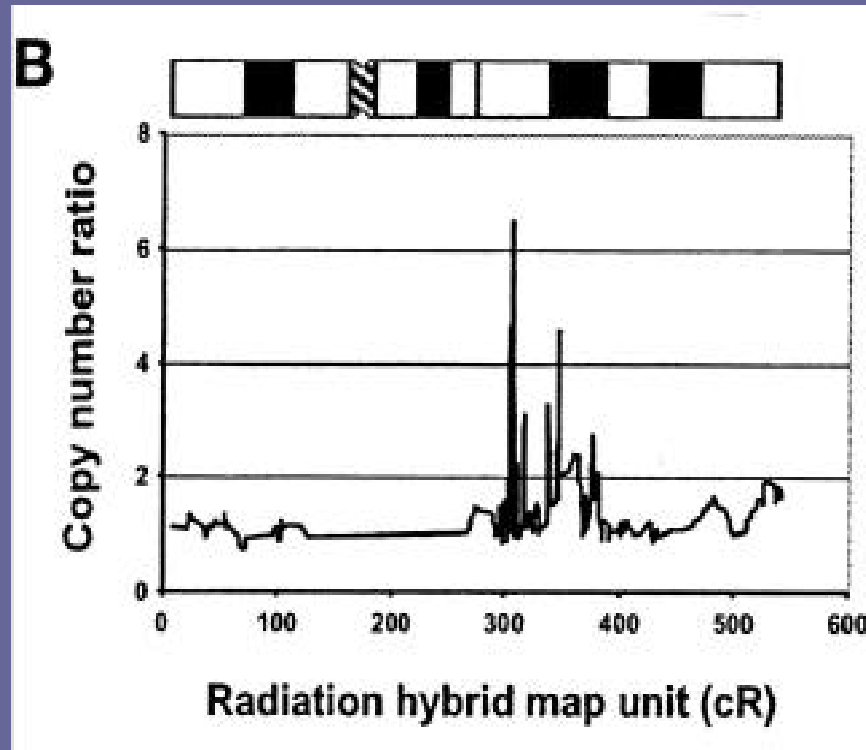
Cancer Genetics Branch

CGH BAC ARRAYS

Pinkel D et al., Nature Genetics 20, 207 - 211 ,1998.

CGH BAC ARRAYS

Bruder CE et al., Hum Mol Genet. 2001;10:271-82.

CGH cDNA

Kauraniemi P et al., Cancer Res. 2001 ;61:8235-40.

CGH cDNA

Kauraniemi P et al., Cancer Res. 2001

DNA Microarray Applications

- **Resequencing**

  Mutations
  Polymorphisms

- **Gene copy number**

- **Gene expression**

High throughput analysis of gene expression

- **cDNA library sequencing**

- **Serial analysis of gene expression (SAGE**

- **Microarray hybridization**

STRATEGIES FOR SIGNAL GENERATION FROM mRNA

• Fluorochrome conjugated cDNA

• Ligand substituted nucleotides with secondary dete

• Radioactivity

• RNA amplification

Oligo versus cDNA Arrays for Expression Analysis

Oligonucleotide Arrays: Pros

- Complete control over sequence

- Sequence and geometric perfection

- Extremely high feature density

Oligonucleotide Arrays: Cons

- **Lack of Flexibility in Some Formats**

- **Absolute Requirement for Sequence Da**

- **Risk of uneven Performance by Individual Array Elements (Lack of Oligo Picking Rules)**

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cDNA Arrays: Pros

- **High Degree of Flexibility**

- **Sequence Independent**

- **High Stringency Hybridization**

- **High Signal Intensity: No Need for Signal Amplification**

cDNA Arrays: Cons

- **Clone Availability**

- **Clone Handling**

- **Clone Authentication**

- **Possible Cross-hybridization**
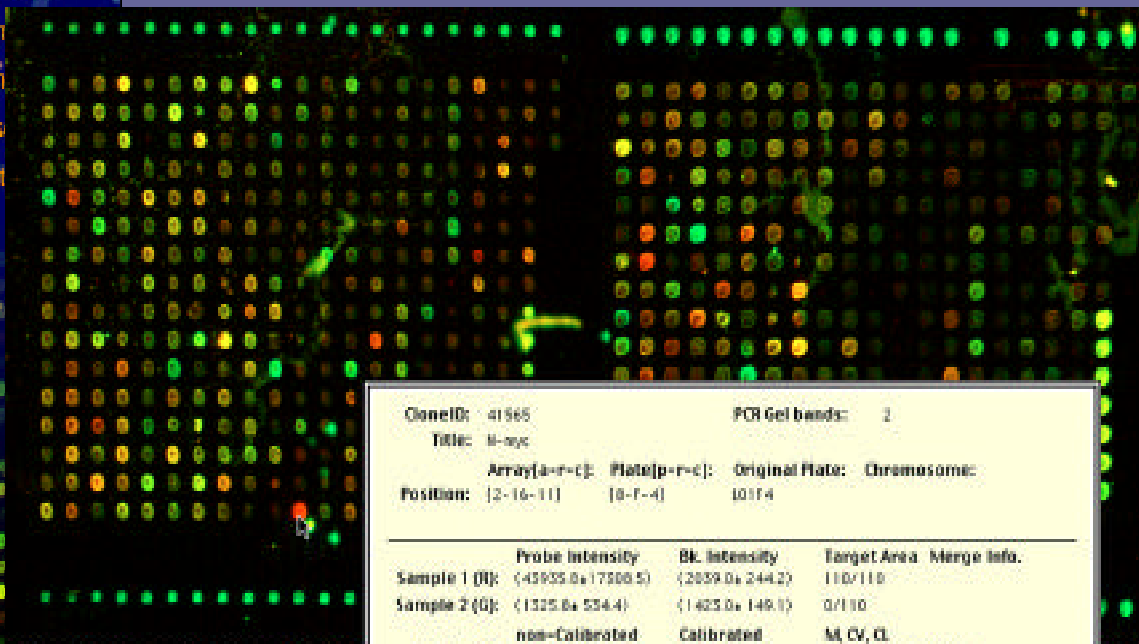
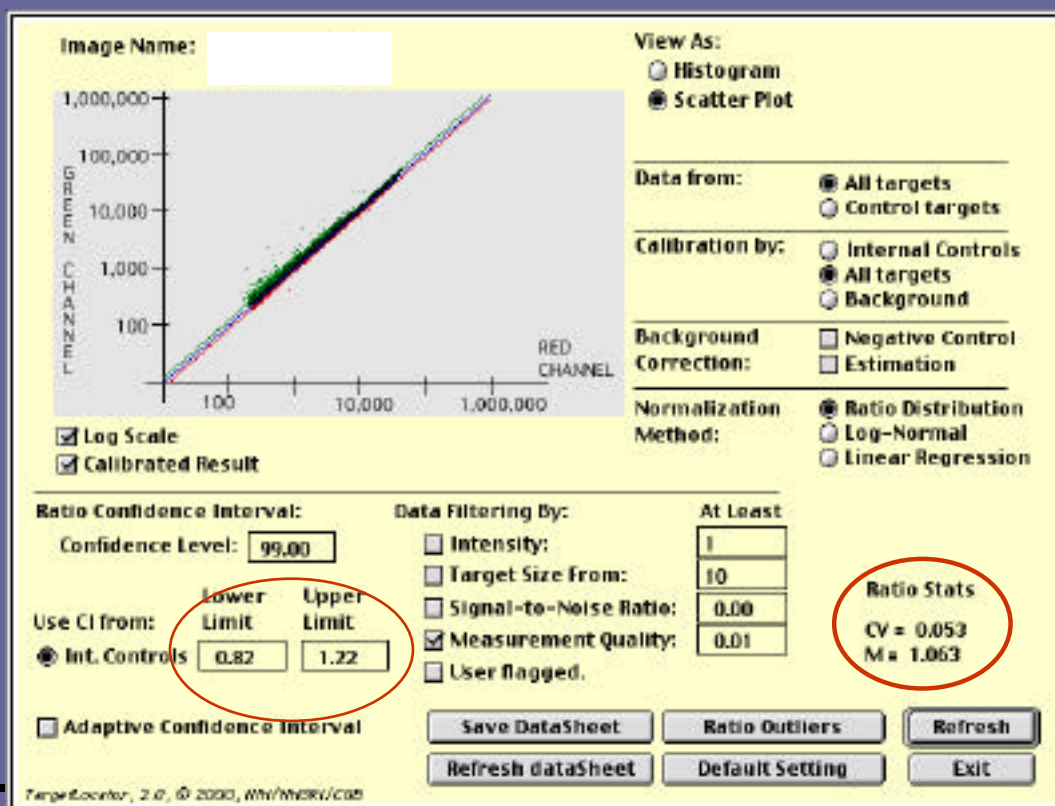# Image Analysis: DeArray

Grid Overlay

Target detection

Image Analysis: DeArray

CloneID:	41565		PCR Gel bands:	2
Title:	N-myc			
	Array[a-r-c]:	Plate[p-r-c]:	Original Plate:	Chromosome:
Position:	[2-16-11]	[0-F-4]	101F4	

	Probe Intensity	Bk. Intensity	Target Area	Merge Info.
Sample 1 (R):	(45935.0±17300.5)	(2039.0±244.2)	110/110	
Sample 2 (G):	(1325.0±554.4)	(1423.0±149.1)	0/110	
	non-Calibrated	Calibrated	M, CV, CL	
Ratio R/G:	33.140	38.709	0.856, 0.258, 99.00%	
Interval:	[0.261, 2.825]	[0.305, 3.297]		

TargetLocator, 1.0, © 1997, NIH/NHGRI/CGB

DATA QUALITY IS CRITICAL

Output of cDNA microarrays: expression ratio

Output of oligonucleotide arrays: expression lev

Both types of data can be analyzed with essentially the same tools.

Normalization of cDNA microarrays:
•global
•housekeeping
•spiked standards

Normalization of oligonucleotide arrays:
•global

Building Expression Arrays

- Completely sequenced and annotated organisms

- Complete gene list unavailable

Expressed Sequence Tags

- Partial, inaccurate cDNA sequences

- Redundancy allows clustering by gene

- Incomplete representation of genome

Clustering of Human ESTs

Final Number of Clusters (sets) (Unigene 146)

====================================

96109   sets total

21857   sets contain at least one known gene
94916   sets contain at least one EST
20664   sets contain both genes and ESTs

• 1193 genes are not represented by an identifiable EST.

Histogram of cluster sizes for UniGene build 146

96,000 clusters

Cluster size	Number of clusters
1	33700
2	13467
3-4	15267
5-8	10197
9-16	5777
17-32	3894
33-64	3549
65-128	4031
129-256	3718
257-512	1732
513-1024	537
1025-2048	162
2049-4096	56
4097-8192	19
8193-16384	3

Expressed Sequence Tags: Options for Array Constructi

- •"Standard" clone sets

- • Custom clone sets

- • Synthetic oligonucleotides

Accessing Expression Data

- •Individual Lab and Journal Sites

APPLICATIONS OF EXPRESSION ARRAYS

•Direct comparisons (Induction)

Biological system critical

•Expression profiling

Requires statistical tools

Power arises from increasing sample number

APPLICATIONS OF EXPRESSION ARRAYS

•Statistical tools for large datasets

•First generation approaches.

APPLICATIONS OF EXPRESSION ARRAYS : TUMOR PROFILING

- Towards a molecular taxonomy of cancer

- Methods lead to gene identification

- Individualized diagnosis and therapy

APPLICATIONS OF EXPRESSIONARRAYS : GENE IDENTIFICATION

- Groups of genes
  - Pathways
  - Co-regulated
  - Correlate with copy #
  - Correlate clinically

- Candidate disease genes

APPLICATIONS OF EXPRESSION ARRAYS: TUMOR PROFILING

- Clustering
  - Unsupervised
  - Supervised
- Classification

- Can classify with respect to any clinically interesting variable

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Alveolar Rhabdomyosarcoma

Pax3
chromosome 2

Method

- Compared 7 ARMS with 6 unrelated cancers cell lines

- Using cDNA microarray containing 1238 elements
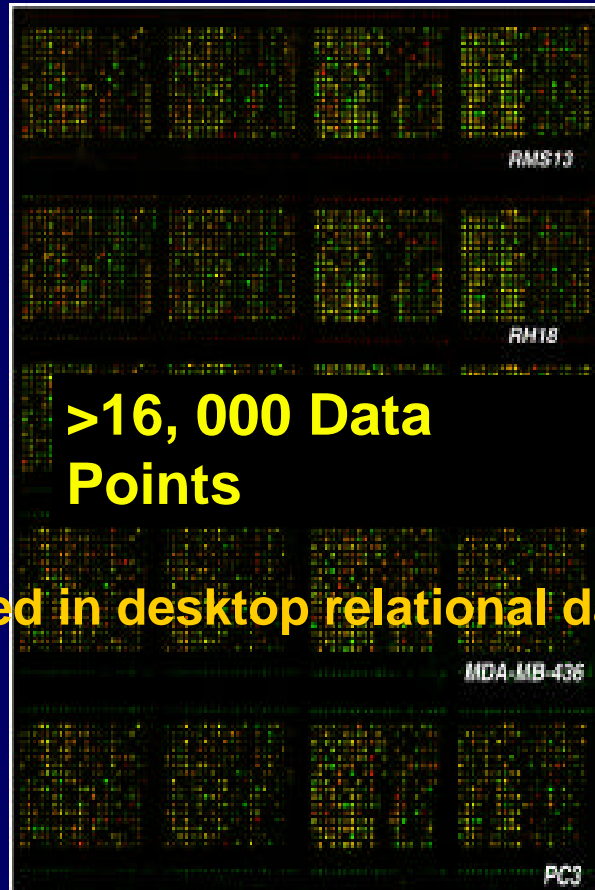
Cell Line Characteristics

Cell Line	Pax3-FKHR	Diagnosis
ARMS1	+	ARMS
RH3	+	ARMS
RH4	+	ARMS
RH5	+	ARMS
RMS18	+	ARMS
RMS13	+	ARMS
RH28	+	ARMS
A204	-	Undifferentiated Sarcoma
NGP127	-	Neuroblastoma
TC71	-	Ewing's Sarcoma
UACC-903	-	Melanoma
PC3	-	Prostate Carcinoma
MDA-MB-436	-	Breast Carcinoma
Control		
NIL-C	-	Fibroblast

Results
- **13 Experiments**
- **1238 genes**

RMS13

RH18

>16, 000 Data Points

Data placed in desktop relational database

MDA-MB-436

PC3

SCATTER PLOT

ARMS

	RH4	RH5	RH3	RH28	RH18	ARMS1
RMS13	r=0.78	**r=0.77**	r=0.69	r=0.78	r=0.73	r=0.68
RMS13	r=0.58	**r=0.40**	r=0.48	r=0.44	r=0.46	r=0.35
	TC71	PC3	MDA-MB-435	JACC-903	NGP127	A204

NON-ARMS

Matrix of Pearson Correlation Coefficients
Distance Map
78 pair-wise comparisons

	RH3	RH4	RH5	RMS13	RH18	**RH28**	A204	NGP127	TC71	UACC-903	MDA-MB-436	PC3
ARMS1	0.547	0.606	0.725	0.683	0.634	0.375	0.307	0.39	0.498	0.426	0.417	0.314
RH3		0.760	0.726	0.69		**0.807**		0.565	0.566	0.391	0.452	0.403
RH4		0.771	0.778	0.67		0.541	0.486	0.558	0.468	0.555	0.476
RH5			0.769	0.667	0.751	0.37	0.486	0.607	0.43	0.532	0.447
RMS13				0.731	0.746	0.35	0.463	0.582	0.446	0.475	0.404
RH18					0.703	0.274	0.281	0.549	0.389	0.405	0.36
RH28						0.417	0.493	0.644	0.479	0.478	0.42
A204							0.426	0.361	0.398	0.368	0.377
NGP127								0.352	0.241	0.371	0.368
TC71									0.46	0.456	0.472
UACC-903										0.507	0.538
MDA-MB-436											0.662
PC3											

Hierarchical Clustering Dendrogram

G
E
N
E
S

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Multidimensional Scaling

	Seattle	L.A.	Houston	D.C.
Seattle	0		1,200	2,500
L.A.		0	1,500	2,800 / 2,600
Houston			0	1400
D.C.				0

	Exp1	Exp2	Exp3	Exp4
Exp1	0	0.50	0.25	0.05
Exp2		0	0.50	0.55
Exp3			0	0.60
Exp4				0

Seattle
D.C.
L.A.
Houston

Exp4
Exp1
Exp2
Exp3

Multidimensional Scaling Analysis

NGP127
A204
RH3
RH28
RH4
ARMS1
MDA-MB436
RH5   RMS13
PC3
RH18
TC71
UACC-903

CLASS DISCOVERY IN MELANOMA

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How subtle a difference in pattern could be reliably detected?

The similarity of the results of the 8 duplicate experiments would put all of these samples within the volume of the central blue sphere.

Cancer Genetics Branch

Weighted List

ARTICLES

Classification and diagnostic prediction of cancers using gene expression profiling and artificial neural networks

JAVED KHAN[1,2], JUN S. WEI[1], MARKUS RINGNÉR[1,3], LAO H. SAAL[1], MARC LADANYI[4], FRANK WESTERMANN[5], FRANK BERTHOLD[6], MANFRED SCHWAB[5], CRISTINA R. ANTONESCU[4], CARSTEN PETERSON[3] & PAUL S. MELTZER[1]

[1]Cancer Genetics Branch, National Human Genome Research Institute, National Institutes of Health, Bethesda, Maryland, USA
[2]Pediatric Oncology Branch, Advanced Technology Center, National Cancer Institute, Gaithersburg, Maryland, USA
[3]Complex Systems Division, Department of Theoretical Physics, Lund University, Lund, Sweden
[4]Department of Pathology, Memorial Sloan-Kettering Cancer Center, New York, New York, USA
[5]Department of Cytogenetics, German Cancer Research Center, Heidelberg, Germany
[6]Department of Pediatrics, Klinik für Kinderheilkunde der Universität zu Köln, Köln, Germany
J.K., J.S.W. and M.R. contributed equally to this study.
Correspondence should be addressed to J.K. or P.S.M.; email: khanjav@mail.nih.gov or pmeltzer@nhgri.nih.gov

Molecular Taxonomy of Small Round Blue Cell Tumors

Hypothesis

- Using cDNA microarrays we can identify
  the genes whose expression level is
- Utilize these genes to classify the characteristic for that cancer & type
  small blue round cell tumors into the
  correct diagnostic categories

Model: Small Blue Round Cell Tumors

Ewing's

Neuroblastoma

Rhabdomyosarcoma

Lymphoma

cDNA Microarray Analysis

Experiments

Burkitt's Lymphoma	8
EWS-Tumor	13
EWS-Cell line	10
Neuroblastoma	12
RMS-Tumor	10
RMS-Cell line	10
Test Unknown	25

>500, 000 Data Points

cDNA microarray
4,000 sequence verified known genes
2,567 sequence verified EST
6,567 genes

Artificial Neural Networks

Pattern Recognition

Training

ANN Output
(96 Genes)

EWS

Classification 100%

RM
S

NB

BL

Table 1 Training sample characteristics

Sensitivity Measurement
Ranked Genes

High Sensitivity
High Rank

1

0

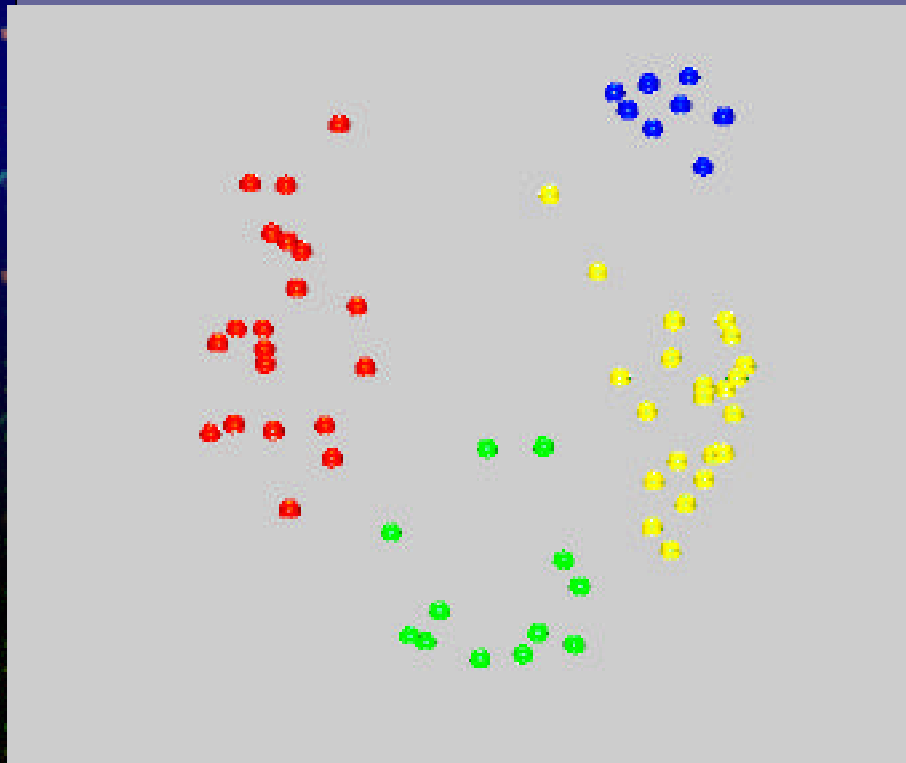ANN Output

Gene Expression

Sensitivity Measurement Ranked Genes

Gene Minimization

MULTIDIMENSIONAL SCALING

- Lymphoma
- RMS
- NBL
- EWS

Cancer Genetics Branch

Artificial Neural Networks

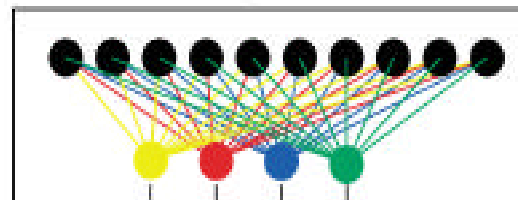## Recalibrate with Top 96 Genes

Diagnosis?

63 training+ 25 "unknown"

96 genes

↓

PCA (10)

↓

Input

EWS RMS BL NB

Output

Diagnostic Classification

WHAT HAVE WE LEARNED FROM THE EXPRESSION PROFILING OF CANCERS SO FAR?

- DISTINCT HISTOLOGIES HAVE DISTINCT PATTERNS OF GENE EXPRESSION.

- USING EXPRESSION DATA IT IS POSSIBLE TO DEVELOP ROBUST FORMAL DIAGNOSTIC CLASSIFIERS.

- NOVEL SUBGROUPS CAN BE RECOGNIZED WITHOUT PREVIOUSLY DEFINED HISTOPATHOLOGIC CORRELATES.

- CLINICALLY USEFUL CATEGORIES CAN BE DEFINED, BUT DO NOT NECESSARILY REQUIRE ARRAYS FOR EVERYDAY CLINICAL IDENTIFICATION.

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WHAT WE HOPE TO LEARN IN THE FUTURE

• IMPROVE THE DIAGNOSTIC CATEGORIZATION
OF TUMORS.

• IDENTIFY USEFUL PREDICTIVE MARKERS FOR
OUTCOME AND THERAPEUTIC RESPONSE
(ARRAY OR CONVENTIONAL).

• IDENTIFY POINTS FOR INTERVENTION:

CRITICAL PATHWAYS

DRUG TARGETS

CLINICAL CORRELATIVE STUDIES
USING MICROARRAYS

• DEFINE QUESTION AND PATIENT SAMPLE.

• APPROPRIATE AND RIGOROUS STATISTICAL
ANALYSIS OF ARRAY DATA.

• RESULT: GENES WHICH CARRY INFORMATION
RELEVANT TO QUESTION POSED.

• DEVELOP FORMAL CLASSIFIER.

• VALIDATE ON ADDITIONAL SAMPLE SET.

MODEL SYSTEM WITH CLEAR THERAPEUTIC IMPLICATIONS:
GASTROINTESTINAL STROMAL TUMOR

- RELATED TO THE INTERSTITIAL CELLS OF CAJAL

- KIT MUTATIONS

- STI-571 SENSITIVITY

- THE BEST "CREDENTIALED" TARGETS ARE THOSE ACTIVATED BY MUTATION.
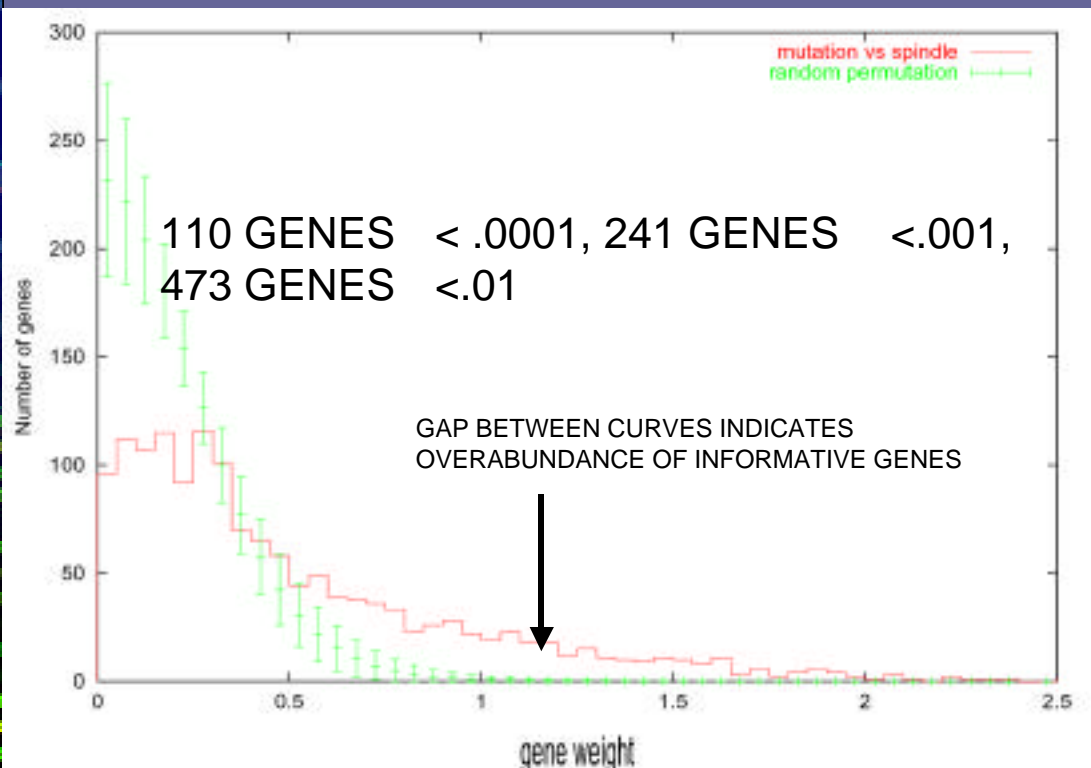
SAMPLES

- 13 MALIGNANT GISTs

- ALL KIT POSITIVE BY IHC

- ALL WITH KIT MUTATIONS

- 4 GUT WALL PRIMARIES

- 8 INTRA-ABDOMINAL EXTENSION

- 1 LIVER METASTASIS

- 6 COMPARISON TUMORS: EXTRA-GI SPINDLE CELL MORPHOLOGY

ARRAYS AND DATA ANALYSIS

- 13,824 ELEMENT SPOTTED cDNA ARRAYS

- OSA REFERENCE PROBE

- GENES RANKED FOR EXPRESSION IN GIST

- WEIGHTED DISCRIMINATOR LIST

- MDS AND HIERARCHICAL CLUSTERING

OVERABUNDANCE OF INFORMATIVE GENES

110 GENES < .0001, 241 GENES <.001, 473 GENES <.01

GAP BETWEEN CURVES INDICATES OVERABUNDANCE OF INFORMATIVE GENES
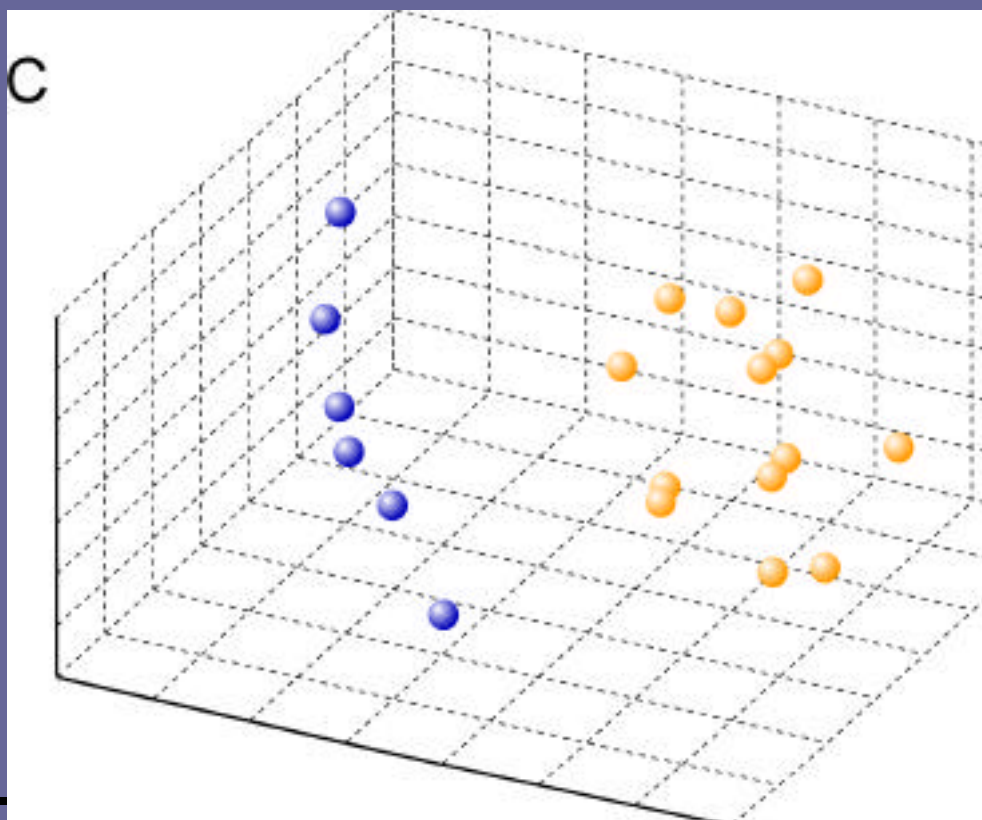
DATA ANALYSIS

- PREFILTER FOR QUALITY AND IDENTIFY GENES HIGHLY EXPRESSED IN GIST: 1987 GENES

- RANK BY WEIGHTED DISCRIMINATOR METHOD
  $w(g, \pm) = \mu_{+}(g) - \mu_{-}(g) \, /[\sigma_{+}(g) + \sigma_{-}(g)]$

- RANDOM PERMUTATION TEST (10^5 trials)
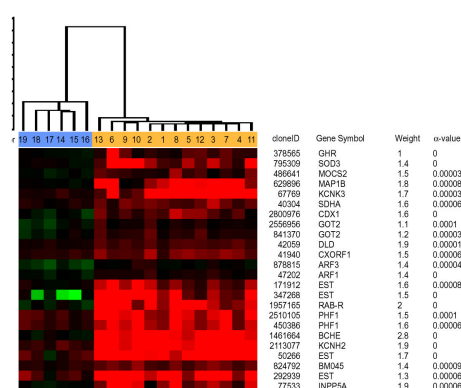
- CLUSTER ANALYSIS USING DISCRIMINATORS

MDS PLOT

C

TOP DISCRIMINATORS FOR GIST

Rank	Weight	Alpha	Gene Description
1	7.55575	0	v-kit sarcoma oncogene
2	6.48306	0	G coupled receptor 20
3	4.60057	0	G coupled receptor 20
4	4.51681	0	annexin A3
5	3.33057	0	KIAA0353 protein
6	3.31734	0	phosphofructokinase, muscle
7	2.95095	0.00008	DKFZP434N161 protein
8	2.83435	0	protein kinase C, theta
9	2.79721	0	butyrylcholinesterase
10	2.72752	0	annexin A3

	Gene Symbol	Weight	α-value
	PFKM	3.3	0
489626	DMN	3.3	0
1161564	ANXA3	4.5	0
2469213	GPR20	6.5	0
2568905	KIT	7.6	0
269806	PTP4A3	2.6	0
375827	SCG2	2.6	0
174627	PRKCQ	2.8	0
205239	TNFRSF6B	2	0
2832322	PRKCQ	2.6	0
2164126			

CONCLUSIONS

• MALIGNANT GISTS EXHIBIT A DISTINCT AND HIGHLY COHERENT GENE EXPRESSION PROFILE.

• THIS GENE LIST IS RELEVANT BOTH TO GIST GROWTH AND NORMAL ICC FUNCTION.

• KIT, A CRITICAL GENE IN REGULATING GIST GROWTH, IS THE BEST DISCRIMINATOR FOR THIS DISEASE.

• EXTENDING THIS APPROACH TO OTHER CANCERS MAY HELP IDENTIFY NEW DISEASE SPECIFIC DRUG TARGETS.

A RECURRING PROBLEM

Oncogenes

Transcription factors

Hormones/growth factors

Drugs

Toxins

Radiation

?????

Downstream Genes

•**Direct targets**

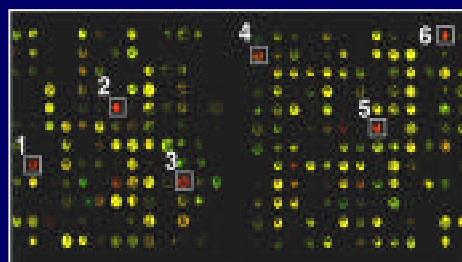•**Indirect targets**

Retrovirus es:

Empty vector
Pax3
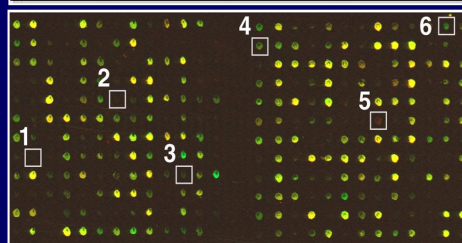**Pax3-Fkhr**

RESULTS

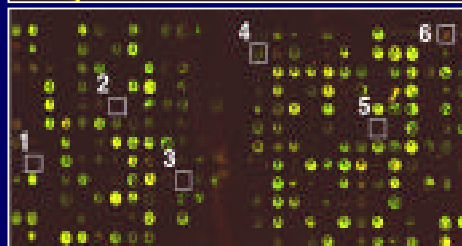**Mouse cDNA array 2200 genes**

PAX3-FKHR
vs
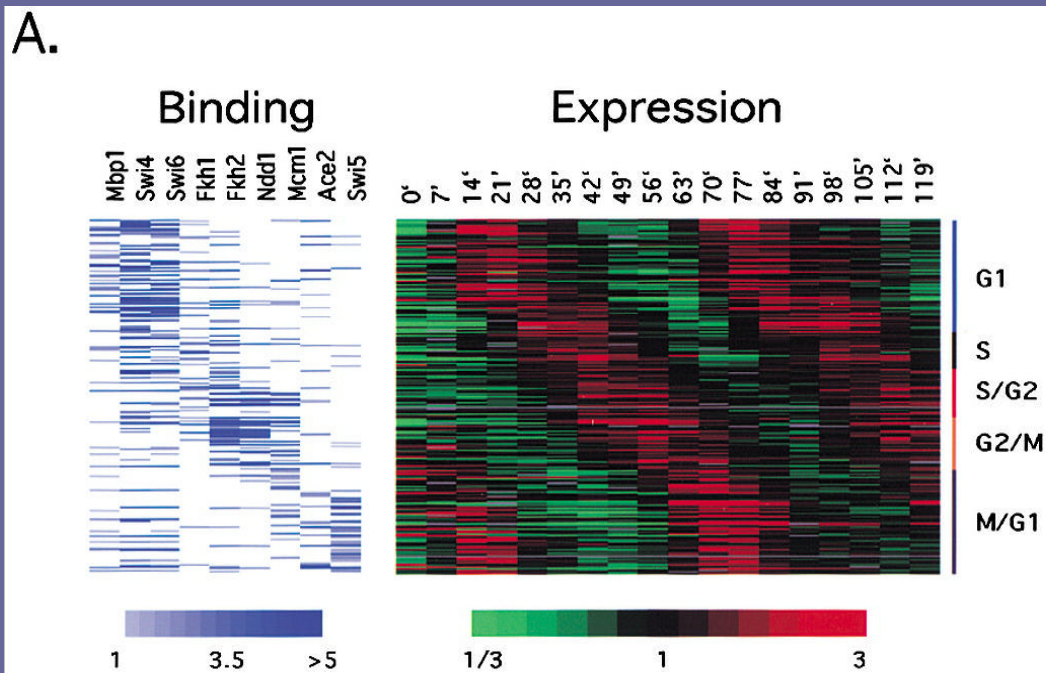**Empty Vector**

PAX3
vs
Empty Vector

3T3 PARENT
vs
Empty Vector

1. Troponin C
2. IGFBP5
3. Myogenin
4. Six1
5. Troponin T
6. IGF2

Promoter Occupancy During Yeast Cell Cycle

Simon I Cell. 2001 Sep 21;106(6):697-708.

Future Promise

• **Numerous clever applications to additional systems, new
computational tools and technical innovations.**
• **Development of large clinically annotated datasets
which allow precise definition of patient subsets and
lead to the identification of new therapeutic targets.**

• **Linking genomic sequence to expression data to define
regulatory elements/transcription factors associated with
co-regulated genes.**

•**Development of computational tools which allow
predictive
modeling of gene networks.**
•**Introduction of technologies which increases the
dimensionality of expression data: protein arrays; cell
arrays; promoter arrays.**